“A discrete choice approach to model credit card fraud”

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Abstract

This paper analyzes the demographic, socio-economic and banking-specific determinants that influence the risk of fraud in a portfolio of credit cards. The study is based on a large banking portfolio and is the first to analyze the statistical significance of the determinants of credit card fraud in Italy. A logit framework is employed that incorporates cards at a risk of fraud as the dependent variable and a set of control variables (e.g., gender, location, credit line, number of transactions in euros and in non-euros currency). The empirical results provide useful indicators on the factors that are responsible for potential risk of fraud. Overall, the riskier categories are women, customers residing in the Center of Italy, those who own a II circuit credit card and secondary owners.

Keywords: credit card, fraud, demographic and socio-economic factors, logit modeling.
JEL Classification: D12, G21, C35.

Introduction

The current global recession is highlighting the fragility of the global banking and finance system that is subject to a greater risk and acts of fraud. There are new challenges in tackling fraud stemming from a fast changing information technology environment, where the internet has become one of the most important channels for the retail sector. Kageyama (2009) reports that in the past three years more than 900 companies surveyed at a worldwide level have lost an average of 8.2 billion dollars a year, a 22% increase with respect to the previously published research. Moreover, the percentage of firms that registered at least one fraud in 2008 has reached 85% that is an 80% increase in the previous year. While these figures hide the motivation for fraud, the rates of growth are significant and in a time of recession this rate is more likely to increase as higher numbers of individuals commit fraud (Abbey, 2009).

In 2005, the world's two largest credit card circuits, Visa and MasterCard, reported 1.14 billion dollars of fraud losses that represented a 62.9% increase with respect to 1995. In the United Kingdom, for example, credit card fraud is one of the fastest growing crimes and in 2008, total card fraud losses amounted to more than 609 million pounds, of which 52.5 million was attributed specifically to online banking fraud (Association for Payment Clearing Services, APACS, 2009b). Arguably, these high amounts can be partially explained by the high volume of transactions and remarkable growth in credit cards ownership over the past three decades. Visa (2003) calculates a 10% year on year compound growth since cards were first issued. The USA, for instance, denotes the highest number of issued cards (more than 1.5 billion) and each inhabitant owns on average more than 5 payment instruments. In Europe, however, the average card holder owns 1.3 cards and the UK confirms its predominance with 22.3% of all EU cards and 2.4 cards per capita (Assofin-Crif-Eurisko, 2008). Such important fraud losses are driving increasing efforts in both the detection and prevention of fraud and the implementation of robust risk management practices in the credit card industry.

In this paper, credit card fraud is defined as "the misuse of a card – without authorization or unapproved purchases – or the counterfeiting of cards" (Wells, 2007). The motivation and opportunity behind credit card fraud are many and varied. Traditional types of fraudulent behavior such as identity theft relate to family members or people that can easily access individual's mail and personal information and committing fraud either by applying for a card or taking over the existing account. Dumpster diving or trashing, where criminals raid rubbish bins to search for credit card details and other sensitive information is becoming more widespread. Lost or stolen credit cards may also be used fraudulently. Skimming of the magnetic stripe is also still practiced either using highly sophisticated devices embedded in ATM's or POS or using simple hand held skimmers capable of storing magnetic stripe data.

Internet enabled fraud is also growing; phishing attacks continue to harvest credit card users' details and compromized computers with key loggers provide organized criminals with the card details. As the vast majority of all credit card transactions are now authorized and cleared on-line, hacking into the e-payment chain to intercept data can harvest many millions of card details. The e-fraud market has grown. Criminals are now provided with various internet resources to counterfeit credit cards, examples are tipping, custom embossing, decoding machines as well as software such as Creditmaster. A common practice is also that of phishing where fraudulent emails hijacking brand name of banks, credit cards companies, etc. are sent aimed at acquiring trickily financial data, account usernames and passwords. Organized crime is normally composed of professional criminals that are setting "carding

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forums" where it is possible to buy wide-scale global stolen personal and financial information. This practice that leads to the unauthorized use of sensitive information to purchase goods and services often involves thousands and even millions of victims (Peretti, 2008). Indeed, credit card fraud is subject to technological enhancement and it is in a continuous evolution.

However, due to the lack of statistical information on fraud – MasterCard, for example, is the only international circuit that provides statistical information on credit card fraud – few microeconomics studies are available in this field. The purpose of this paper is to analyze the demographic, socio-economic and banking-specific determinants that influence the risk of a credit card fraud. The empirical investigation is based on a unique dataset containing approximately 320,000 observations from a recent credit card portfolio issued in Italy. In 2004, MasterCard reported that the percentage of fraud in all European countries was approximately 0.07% of card holder expenditure while in Italy this figure was 0.05% (Affari & Finanza, 2009). The Association for Payment Clearing Services (APACS, 2009a) reports that at a worldwide level Italy is one of the top five countries to have seen an increase in the use of fraudulent UK credit cards. Fraud on UK-issued cards being used in Italy has increased by 72.9% since 2005, to £8.3 million in 2008.

For the portfolio of cards under study, the empirical analysis is performed on the risk of fraud across three product categories that are classic, gold and revolving. The econometric approach is based on a logit framework, where the probability that a given credit card experiences a fraud is estimated. The dichotomous dependent variable is regressed on a set of explanatory variables (e.g., gender, location, outstanding balance, number of transactions in euros and non euros). The empirical results provide useful indicators on the factors that are likely to influence fraud events based on the available sample. Hence, this framework offers not only a microeconomics perspective to analyze the risk of a fraudulent behavior but most importantly an approach to help risk managers in fraud prevention by providing insight into which factors may lead to fraudulent events.

The paper is organized as follows. In the next section, a literature review on credit cards fraud is provided. In the second section the methodology employed is highlighted. In the third section, main empirical results are provided and concluding remarks are given in the last section.

1. A literature review on credit card fraud

Fraud literature, that first appeared in the 1980s, treated a wide range of economic activities such as insurance fraud (Dionne, 1984; Clarke, 1989; Artís, Ayuso and Gillén, 1999; Caudill, Ayuso and Gullén, 2005; Boyer, 2007), medical fraud (Pontell and Geis, 1982; Feldman, 2001; Rai, 2001) and accounting fraud (Beasley, 1996; Gerety and Lehn, 1997; Sadka, 2006; Crutchley et al., 2007). Though fraudulent behavior has been analyzed in financial markets (particularly for securities, bankruptcy and money laundering), very few studies exist on credit card fraud.

One of the first papers that appeared in the law and criminology literature on credit card fraud (Caminer, 1985) emphasized the need to allow authorities greater access to issuer records and to the USA federal government to devote greater resources to the investigation of credit card fraud. Hence, since the 80's there has been the belief that credit card fraud was increasing at an astounding rate and losses were borne by customers themselves. It is interesting to note that in Italy over 20 years after the Caminer's appeal, all card issuers are obliged to report all credit card fraud into a central database (Decreto, 2007).

As Bolton and Hand (2002) point out, it is important to distinguish between fraud prevention, that is measures to stop fraud occurring in the first place and fraud detection, that is measures to identify fraud as quickly as possible, once it has been perpetrated (for a literature review, see Delamaire, Abdou and Pointon, 2009).

Very few studies analyze how to prevent fraud occurring in the first place. Masuda (1993), for example, reports a successful retail strategy in credit card fraud prevention. There is evidence that program initiatives and an industry-wide action with the exchange of fraud-related intelligence data amongst regional and national authorities seem to be the key to reduce credit card fraud. Williams (2007) presents a case study of credit card fraud in Trinidad and Tobago, new entry countries into the credit card market, in which a prevention activity can be improved by issuing specific laws, educating and informing the public of the various fraudulent typologies and enhancing the critical role of the banking associations in formulating *ad hoc* principles and policies to control this type of crime. Barker, D'Amato and Sheridon (2008) describe numerous schemes and techniques and give additional ones. However, detection and prevention cannot be always regarded as distinct actions. To a certain extent it is possible to learn from the past fraud patterns in order to prevent similar cases occurring in the future. To this aim, several statistical techniques are available such as linear regressions, classification trees, naïve Bayes, neural networks and self-organizing maps (SOM) that are based on the clustering capabilities of neural networks (Thomas, Oliver and Hand, 2005). These techniques are aimed at discriminating if a new credit card transaction belongs to the genuine set or to the fraudulent set. More recently, Quah and Sriganesh

(2008) propose a real-time fraud detection and present a new approach to analyze card owners' behavior for detection of fraud.

In the literature, a commonly used technique to detect credit fraud is logistic regression. Such an econometric tool, together with the above mentioned techniques, is mostly employed within the credit scoring process to help institutions and organizations decide whether to issue credit to consumers who apply for it (Desai, Crook and Overstreet, 1996; Greene, 1998; Thomas, 2000; Crook and Banasik, 2004; Abdu, 2009; Šušteršič et al., 2009).

From the present literature review, it emerges that empirical studies are mainly concentrated on a priori understanding of whether or not to provide consumers with a given bank product (such as a credit card or loan). However, very few papers employ microeconomics bank data to analyze the factors that influence the risk of fraud in a portfolio of credit cards. In a recent study, Hartmann-Wendels, Mählmann and Versen (2009) make use of a sample of approximately 200 thousand observations, on successful applicants from a German internet-only bank, to analyze what factors do affect fraud. The main finding is that fraud risk is highly influenced by determinants such as gender, civil status, age, occupation and urbanization. Above all, nationality matters as foreign customers are 22.25 times more likely to perpetrate a fraud than nationals. Hence, the present paper aims at expanding this strand of research, providing new evidence on the main factors affecting the risk of fraud within the Italian credit card market, through the analysis of an extensive credit card data set at a microeconomic level.

2. Methodology

2.1. Definitions and data. In 2008, credit cards in Italy represented around 45% of the total card payment system (DataBank, 2009). The empirical model presented in this study makes use of banking microeconomic data on only three types of credit cards: classic, gold and revolving. Mass market credit cards, sometimes referred to as "classic cards", are well-spread worldwide and have standard characteristics; relatively limited availability to spend, POS and ATM functionality and low or no annual fees. Gold credit cards are generally held by customers that are more likely to have higher incomes and a higher spending propensity. This typology of card is, in fact, characterized by higher joining and annual fees, higher spending limits and daily cash withdrawal limits since they often provide extra services such as travel insurance, roadside assistance, hotel and car-rental advantages, air travelling executive privileges, world wide support in the event of loss or theft of the card, etc. The gold card can be thought as a more sophisticated classic where the additional services are mandated by the international circuit. A revolving card is often similar to the classic, or the gold card, but allows the customer to spread the payment over a series of billing cycles for a fee or interest charges. The owner of the revolving card, therefore, has the need to borrow or control the way the debt is repaid. This payment instrument is more likely to be influenced by economic turmoil (Assofin-Crif-Eurisko, 2009).

The empirical model that follows is tested using data collected from recent bank card account archives for an Italian based issuer. The cards were issued on principle global circuits. Approximately, 320 thousands card positions are considered. Each observation can be thought as a photo of each client that summarizes their position. It is important to note that this paper employs data on actual positions, and hence, one can derive a static analysis on consumers' preferences. Classic and gold cards, issued to clients that hold a current account with the issuer, represent 60.1% and 3.4%, respectively, of the positions. The revolving cards, 36.5% of the positions, were issued after a credit scoring procedure applied by the bank. In this circumstance, it is possible that the use of *ex post* data, only with selected individuals, leads to biased estimates of the probability to acquire a given payment instrument. This issue is not uncommon in the literature. Hartmann-Wendels, Mählmann and Versen (2009), for example, make use of a sample of approximately 200 thousands successful applicants from a German internet-only bank, to analyze what factors affected fraud. Hence, even factors that do not explicitly enter the acceptance scoring process, but are at the same time correlated with the variables in the fraud equation may cause biased predictions. However, as in this case, no data on rejected applications are available. Nevertheless, the findings emerging from actual data on successful applications can shed light on understanding potential fraudulent behavior in credit markets. Besides, from the bank's perspective understanding determinants of fraud risk for the existing customer portfolio is important to risk managers who have to detect, control and prevent credit card fraud.

The dependent variable used in the logit model is risk of fraud where risk of fraud is defined as a situation where there is risk of actual evidence of unauthorized use of a credit card or its details. These include also cards that are reported as stolen that are at risk of fraud.

2.2. The model specification. The aim of the empirical analysis is to estimate the probability that a given type of credit card experiences a risk of fraud. This framework is made operational by using a particular distribution for the disturbances, that is a logit model within a discrete choice structure (Greene, 2003). Formally, a vector of dependent variables is observed $Y_i = (Y_1, Y_2)$. Specifically, if a customer is characterized at risk of fraud (either where the customer is the fraudster or is a victim of fraud), and hence, a given credit card is at a fraud risk, Y_i takes the value of one; likewise, if customer i belongs to the genuine set, and hence, a given credit card is not subject to risk of fraud, then Y_2 takes the value of zero. Because coefficients change from one regime to another, probabilities (P) change leading to a new index (I). In analytical terms:

$$I_i = \beta_0 + \beta_1 X_i + \varepsilon_i \ , \tag{3}$$

$$Y_i = 1 \quad if \quad I_i > 0, \tag{4}$$

$$P(Y_i = 1) = P(I_i > 0) = P(\beta_0 + \beta_1 X_i + \varepsilon_i) > 0 =$$
$$= P(\varepsilon_i > -\beta_0 - \beta_1 X_i) = P_i \int_{-\infty}^{\beta_0+\beta_1 X_i} f(t)dt = F(\beta_0 + \beta_1 X_i), \tag{5}$$

$$P(Y_i = 1 | X) = \frac{e^{\beta_0+\beta_1 X_i}}{1+e^{\beta_0+\beta_1 X_i}} = \Lambda(\beta_0 + \beta_1 X_i), \tag{6}$$

that is the probability of a fraudulent action is assumed to be a function of customers' behavior and a set of determinants defined as $X_{i,.}$ Following the empirical study cited in the literature review section, a description of the set of explanatory variables included into the model (i.e. gender, location, circuit, cardholder, outstanding balance, number of transactions in euros and in non-euros and credit line) is provided in Table 1.

Table 1. List of control variables

Name	Definition	Code
Gender	This dichotomous variable takes the value of one if female, zero if male.	gen
Location	Dummy variables take into account the geographical heterogeneities of Italy. Standard definitions of geographical zones are employed (ISTAT, 2009); North West (nw) – North East (ne) Centre (cen) – South (sou) – Islands (isl) used as the reference group. The locations of the cardholders are given by a mapping of their postal address zip code to geographical zone using tables produced by the Institute Post Office.	nw ne cen sou isl
Circuit	This dummy variable takes one as a value if the card has been issued by the first circuit and zero by the second circuit.	cir
Cardholder	This dummy variable takes the value of one if the credit card has been issued for a secondary owner and zero otherwise.	hl
Outstanding balance	It is given by the sum of all expenditure and charges on the card less the amounts paid. For revolving cards this translates into what the customer still needs to pay off at the end of the billing cycle while for classic and gold cards it is what the customer actually pays at the end of the month. Within the sample, the maximum value is 20,062 euros, while the minimum value is zero euros.	ob
Type of transactions	The number of transactions in euros; within the sample, the minimum value is zero, while the maximum value is 87 transactions. The number of transactions in a foreign currency rather than euro; within the sample, the maximum value is zero, while the maximum value is 58 transactions.	nteu ntneu
Credit line	This is a continuous variable that accounts for the amount of the spending limit of the card. Within the sample, the minimum value is 1,000 euros, while the maximum value is 50,000 euros.	cl

Table 2 provides a statistical description of the dichotomous variables under investigation. The Pearson χ^2 statistics tests for the null hypothesis that the distribution of fraud case does not differ across the categories of the variable. Hence, the result is that all the variables are highly dependent with the risk of fraud.

Table 2. Descriptive statistics of dichotomous variables

	Fraud risk = 0	%	No fraud risk =1	%	Total
Frequency	311,297	98.13	5,934	1.87	317,231
Gender					
Male	190,335	98.37	3,157	1.63	193,492
Female	120,962	97.76	2,777	2.24	123,739
Total	311,297	98.13	5,934	1.87	317,231
Pearson χ2= 154.328 (0.000)					
Location					
NW	8,522	97.61	209	2.39	8,731
NE	136,276	97.64	3,294	2.36	139,570
CEN	13,348	97.13	394	2.87	13,742
SOU	64,748	98.11	1,245	1.89	65,993
IS	88,403	99.11	792	0.89	89,195
Total	311,297	98.13	5934	1.87	317,231
Pearson χ2= 738.868 (0.000)					
Cardholder					
Principal	301,995	98.15	5,686	1.85	307,681
Secondary	9,302	97.40	248	2.60	9,550
Total	311,297	98.13	5,934	1.87	317,231
Pearson χ2= 28.300 (0.000)					
Circuit					
I circuit	204,886	97.55	5,154	2.45	210,040
II circuit	106,411	99.27	780	0.73	107,191
Total	311297	98.13	5934	1.87	317,231
Pearson χ2=	1.20E+03	(0.000)			

Note: p-values are in parentheses.

β_0 and β_1 are the parameters to be estimated; e is the logistic functional form that allows one to ensure that the estimated choice probabilities lie between zero and one; Λ is the cumulative logistic distribution function. The logistic regression is estimated using maximum likelihood.

In discrete choice models, estimated coefficients cannot be interpreted in terms of elasticity. Hence, marginal effects, that represent the impact of a one-unit change in the explanatory variable on the dependent variable, *ceteris paribus*, can be also computed. In analytical terms, given the index I and the probability P:

$$I_i = \beta_0 + \beta_1 X_i + \varepsilon_i, \tag{7}$$

$$P_i = \int_{-\infty}^{\beta_0+\beta_1 X_i} f(t)dt, \tag{8}$$

then the marginal effect of changes in X on this probability is given by:

$$\frac{\partial P_i}{\partial X_i} = f(\beta_0 + \beta_1 X_i)\beta_1. \quad (9)$$

The marginal effect (ME) for dummy variables is computed by employing the means of all the other variables. This gives an accurate measure of elasticity as if the dichotomy variable was a continuous one (Greene, 2003). Regression results are reported in the second column of Table 3.

In the empirical literature, more often, odds ratio and relative risk ratio (RRR) are reported (see, for example, Ardiç and Yüzereroğlu, 2006). On the one hand, the odds ratio for a given group is given by the following expression:

$$exp^{a+b*X}, \quad (10)$$

where X equals zero when the odds ratio refers to the reference group and one otherwise. Odds ratio above one, associated with positive estimated parameters, indicates that higher values of the explanatory variable increase the predicted probability of a given category compared to the reference category. Coefficients less than one indicate the opposite.

For dichotomous variables, the RRR expresses the ratio of the probability of choosing one group category over the probability of choosing the reference group and is given by the following expression:

$$RRR = (group\ category\_odds)/(reference\ group\_odds) \quad (11)$$

see, for example, Hartmann-Wendels et al. (2009).

4. Empirical findings

The main findings from the logit regression are reported in Table 3. With only one exception, all of the coefficients are statistically significant at the 1% level. The overall statistics indicate a well-specified model: the likelihood ratio test (LR(11)) shows that the coefficients of the explanatory variables are jointly statistically significant; the Hosmer-Lemeshow goodness-of-fit test (that is Pearson χ^2) fails to reject the null hypothesis that the distribution fits the data.

Table 3. Logit regression results

	Coefficients	ME	RRR §
Gender (ref. male)			
gen	0.3200***	0.0050***	1.36
Location (ref. Islands)			
nw	0.6384***	0.0130***	1.87
ne	0.5561***	0.0088***	1.74
cent	0.8441***	0.0190***	2.28
sou	0.3332***	0.0060***	1.39
Circuit (ref. I circuit)			
cr	-1.0289***	0.0138***	0.36
Ownership (ref. principal)			
hl	0.2509***	0.0043***	1.28
Outstanding balance			
ob ^	0.0002***	-3.52E-06***	1.000*** ^
Type transactions			
nteu ^	0.0245***	0.0004**	1.025*** ^
ntneu ^	0.0156**	0.0002	1.016
Credit line			
cl ^	0.0000***	6.28E-07***	1.000*** ^
Number of obs.	317231		
Pseudo R^2	0.0337		
LR χ2(11)	1986.33***		
Pearson χ2(11)	44561.75 (p-value 0.998)		
Log likelihood	-28495.967		

Notes: *** and ** indicate statistical significance at the 1% and 5% levels, respectively; § e.g. RRR = (female_odds)/(male_odds) = 0.0137/0.0187 = 1.36; ^ odds ratio.

Considering the first dichotomous variable *gen* (gender), the probability ratio indicates that women are 1.36 times riskier than men. This outcome can be interpreted in a number of ways: women may be more likely to discover and report a fraudulent event than men; their behavior and spending patterns put the card at a greater risk; women may commit more fraud than men. As pointed out by Epaynews (2009), women are more likely to commit fraud in mail order, communications and loans, whereas men fraudsters are more active in areas such as asset finance and insurance.

Location turns to be an important factor in explaining risk fraud in credit cards. Customers who are residents in the Centre of Italy are the riskiest group in comparison to the reference one but also to the other geographical areas. The customers who are residents in the South tend to show a relatively lower risk.

The second circuit is affected only 36% by fraud risk and, hence, the first circuit has 2.75 times more probability to incur in a fraud. This finding is of a particular interest for banking institutions that should closely consider banking-specific features such as the security standards for a given circuit. Besides, this result may also be explained by the risk propensity of the pool of customers inherent to each of the circuits.

As an additional outcome, secondary card owners are significantly more likely to be at risk of fraud (Table 3). In general, secondary card owners are close relatives of the primary owner (e.g., partners, children); these individuals may be less aware of the various fraudulent typologies and are more likely to be at risk.

Overall, the coefficients of the continuous variables (*ob, nteu, ntneu, cl*) are statistically significant at the 1% level, with the only exception for *ntneu*. However, the effects on the risk of fraud are very small, as highlighted by the marginal effects results. According to the odds ratio for *nteu* and *ntneu*, the transactions in euros are slightly riskier than the non-euros transactions.

Conclusions

In the credit market literature, only a few studies make use of banking data to analyze the risk of fraud for a given set of credit cards (i.e. classic, gold and revolving credit cards). In this paper, a logit analysis has been conducted to assess which factors may lead to the risk of fraud. Fraud has been defined as an unauthorized use of a credit card, including card details, and also stolen cards that are potentially at risk of fraud. To this aim, microeconomic data have been employed for more than 300 thousand observations. Data were obtained from recent account archives for bankcards issued throughout Italy. The model has focused on socio-demographic as well as banking-specific factors influencing the probability to incur a risk of fraud. Marginal effects, odds and relative risk ratio have been computed. Overall, the coefficients of the explanatory variables included in the model are statistically significant at the 1% level and the model is well-specified.

The results have shown that the risk of fraud in credit cards is influenced by many determinants: gender, location, type of circuit, card ownership, credit line and number of transactions divided by currency. Women have been found to be riskier than men either as fraudsters or victims of crime. Geographic location also matters. The Centre of Italy denotes customers that are likely to lead to a higher risk of fraud for the bank. Overall, the least risky geographical zone is the Islands.

As a banking-specific feature, transactions within the second circuit have denoted higher standards of security with respect to the first circuit. Furthermore, risk managers should also increase fraud prevention in transactions made by secondary owners who have been found to be 1.28 times riskier than principal owner.

Though the coefficients of the continuous variables (*ob, nteu, cl*) are statistically significant, the marginal effects on fraud risk are quite small. Overall, the transactions in euros are slightly riskier than the non-euro transactions. The empirical findings show that an increase in either the credit line or in the amount the client needs to pay at the end of the billing cycle should not imply a higher risk.

This paper is a novel example of consumer finance research on fraud risk. A discrete choice model has helped to systematically analyze the potential fraudulent behavior within the credit card market, where customers can be considered either as fraudsters or as victims. The empirical findings offer insightful information to risk managers on the characteristics and behavior of their pool of clients and on the potential factors that may lead to fraudulent actions. Bankers can employ actual positions to assess fraud risk and to discriminate customers into the genuine set or the at-risk set. Customers information and education of the various fraudulent typologies seem a key strategy to prevent credit card fraud, particularly for women who are often victims of thefts and secondary owners, as highlighted in the empirical investigation. Risk managers should also closely consider banking-specific features such as standards of security for a given circuit.

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